

# On Projection-Based Model Reduction for the Simulation of Nonlinear Systems

Matthias Heinkenschloss

Department of Computational and Applied Mathematics  
Rice University, Houston, Texas  
heinken@rice.edu

May 20, 2015

Workshop on Model Order Reduction  
of Transport-dominated Phenomena  
TU Berlin, May 19&20, 2015

Funded in part by AFOSR and NSF

# Outline

Motivation

EIM and DEIM

EIM and DEIM for Finite Element Simulations

EIM and DEIM for Navier-Stokes

Error Estimate

# Motivation

- ▶ System (typically discretization of (system of) PDE(s))

$$\mathbf{A}\mathbf{y} + \mathbf{F}(\mathbf{y}; \theta) = \mathbf{B}\mathbf{u} + \mathbf{b}$$

Parameter  $\theta \in \Theta$ , control  $\mathbf{u} \in \mathcal{U}_{ad}$ .

(Both are parameters for purpose of model reduction.)

- ▶ (Deterministic) Optimal control

$$\min J(\mathbf{y}, \mathbf{u})$$

$$\text{s.t. } \mathbf{A}\mathbf{y} + \mathbf{F}(\mathbf{y}; \theta_0) = \mathbf{B}\mathbf{u} + \mathbf{b},$$

$$\mathbf{u} \in \mathcal{U}_{ad}, \mathbf{y} \in \mathcal{Y}_{ad}.$$

- ▶ Optimal control governed by PDEs with uncertain parameters (informal)

$$\min \int_{\Theta} \rho(\theta) J(\mathbf{y}(\theta), \mathbf{u}) d\theta$$

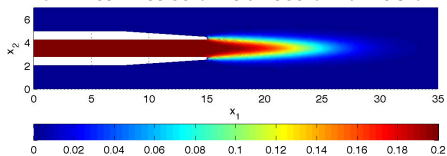
$$\text{s.t. } \mathbf{A}\mathbf{y}(\theta) + \mathbf{F}(\mathbf{y}(\theta); \theta) = \mathbf{B}\mathbf{u} + \mathbf{b}, \quad \theta \in \Theta$$

$$\mathbf{u} \in \mathcal{U}_{ad},$$

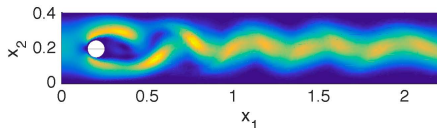
$$\mathbf{y}(\theta) \in \mathcal{Y}_{ad}, \quad \theta \in \Theta.$$

# Examples

## Nonlinear reaction advection diffusion



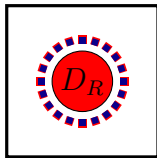
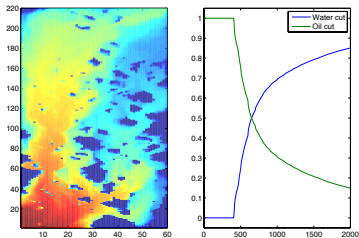
## Flow control



## Direct field acoustic testing



## Reservoir management



Comp. domain, region of interest  $D_R$ , 20 speakers surrounding  $D_R$ .

## In this talk

- ▶ Focus on simulation (solve  $\mathbf{A}\mathbf{y} + \mathbf{F}(\mathbf{y}; \theta) = \mathbf{b}$ ).
- ▶ Detailed aspects of DEIM/EIM in finite element setting.
- ▶ Limits of DEIM/EIM.
- ▶ Error estimates.

# Outline

Motivation

EIM and DEIM

EIM and DEIM for Finite Element Simulations

EIM and DEIM for Navier-Stokes

Error Estimate

# Model Problem

Semilinear Advection-Diffusion-Reaction PDE

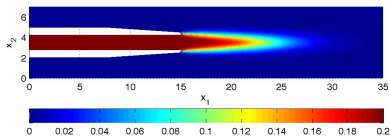
$$\begin{aligned} -\nu\Delta y + \beta \cdot \nabla y + f(y, \theta) &= 0, && \text{in } \Omega, \\ y &= h, && \text{on } \Gamma_D, \\ \nabla y \cdot n &= 0, && \text{on } \Gamma_N. \end{aligned}$$

Consider specific nonlinearity

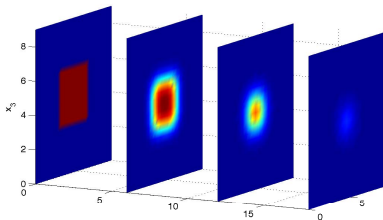
$$f(y, \theta) = Ay(C - y)e^{-E/(D-y)}$$

where  $C, D$  are known constants and  $\theta = (\ln(A), E)$  are system parameters in  $\Theta = [5.00, 7.25] \times [0.05, 0.15] \subset \mathbb{R}^2$ .

2D



3D



► Semilinear Advection-Diffusion-Reaction PDE

$$\begin{aligned} -\nu\Delta y + \beta \cdot \nabla y + f(y, \theta) &= 0, && \text{in } \Omega, \\ y &= g, && \text{on } \Gamma_D, \\ \nabla y \cdot n &= 0, && \text{on } \Gamma_N. \end{aligned}$$

Consider specific nonlinearity

$$f(y, \theta) = Ay(C - y)e^{-E/(D-y)}$$

where  $C, D$  are known constants and  $\theta = (\ln(A), E)$  are system parameters in  $\Theta = [5.00, 7.25] \times [0.05, 0.15] \subset \mathbb{R}^2$ .

► Weak form: Find  $y \in H^1(\Omega)$  with  $y = h$  on  $\Gamma_D$  such that

$$\int_{\Omega} \nu \nabla y \cdot \nabla v dx + \int_{\Omega} \beta \cdot \nabla y v dx + \int_{\Omega} f(y, \theta) v dx = 0$$

for all  $v \in H^1(\Omega)$  with  $v = 0$  on  $\Gamma_D$ .



- ▶ Finite element discretization. Approximate

$$y_h(x) = \sum_{j=1}^N \mathbf{y}_j \phi_j(x) + \sum_{j=N+1}^{N+N_D} g(x_j) \phi_j(x)$$

where  $y_h$  satisfies

$$\int_{\Omega} \nu \nabla y_h \cdot \nabla \phi_i dx + \int_{\Omega} \beta \cdot \nabla y_h \phi_i dx + \int_{\Omega} f(y_h, \theta) \phi_i dx = 0, \quad i = 1, \dots, N.$$

To simplify presentation omit stabilization and often set  $g(x_j) = 0$ .

- ▶ In practice use quadrature to evaluate integrals:  
 $x_\ell \in \bar{\Omega}$ ,  $\varpi_\ell \in \mathbb{R}$ ,  $\ell = 1, \dots, n_q$ , quadrature nodes and weights.

$$F_h(y_h, \phi; \theta) = \sum_{\ell=1}^{n_q} \varpi_\ell f(y_h(x_\ell), \theta) \phi(x_\ell) \left( \approx \int_{\Omega} f(y_h(x), \theta) \phi(x) dx \right).$$

- ▶ Matrix form:

$$\mathbf{A} \mathbf{y} + \mathbf{F}(\mathbf{y}; \theta) = \mathbf{b}.$$

# Basic Reduced Order Model

- ▶ Generate snapshots  $y_{h,i}$ ,  $i = 1, \dots, n$  ( $\mathbf{y}_i$ ,  $i = 1, \dots, n$ )
- ▶ Extract orthonormal basis  $v_{h,i}$ ,  $i = 1, \dots, n$  ( $\mathbf{v}_i$ ,  $i = 1, \dots, n$ ) from snapshots.  $n \ll N$ .
- ▶ Approximate  $\mathbf{y} = \bar{\mathbf{y}} + \mathbf{V}\hat{\mathbf{y}}$ . (To simplify notation set  $\bar{\mathbf{y}} = \mathbf{0}$ .)
- ▶ Reduced order model

$$\underbrace{\mathbf{V}^T \mathbf{A} \mathbf{V}}_{n \times n} \hat{\mathbf{y}} + \mathbf{V}^T \mathbf{F}(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{V}^T \mathbf{b}.$$

where  $\mathbf{V} = (\mathbf{v}_1, \dots, \mathbf{v}_n) \in \mathbb{R}^{N \times n}$ .

- ▶ Approximation of  $\hat{\mathbf{y}} \mapsto \mathbf{V}^T \mathbf{F}(\mathbf{V}\hat{\mathbf{y}}; \theta)$  with (on-line) computational complexity independent of  $N$ .  
EIM: Barrault, Maday, Nguyen, Patera (2004), Grepl et al. (2007).  
DEIM: Chaturantabut, Sorensen (2010).

# DEIM

- ▶ Generate subspace  $\mathbf{U} = [\mathbf{u}_1, \dots, \mathbf{u}_m] \in \mathbb{R}^{N \times m}$  for nonlinear term. Want  $\mathbf{F}(\mathbf{V}\hat{\mathbf{y}}(\theta); \theta) \in R(\mathbf{U})$  approximately for all  $\theta \in \Theta$ .
- ▶ Compute approximation  $\hat{\mathbf{F}}(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{U}\mathbf{c}(\hat{\mathbf{y}}; \theta)$  such that

$$\hat{\mathbf{F}}_i(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{F}_i(\mathbf{V}\hat{\mathbf{y}}; \theta) \text{ for components } i = p_1, \dots, p_m.$$

(Index selection next slide)

- ▶ Define  $\mathbf{P} = [\mathbf{e}_{p_1}, \dots, \mathbf{e}_{p_m}] \in \mathbb{R}^{N \times m}$ ; write interpolation condition as

$$\mathbf{P}^T \hat{\mathbf{F}}(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{P}^T \mathbf{F}(\mathbf{V}\hat{\mathbf{y}}; \theta).$$

- ▶ DEIM approximation of nonlinearity:

$$\hat{\mathbf{F}}(\mathbf{V}\hat{\mathbf{y}}; \theta) \stackrel{\text{def}}{=} \mathbf{U}(\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \mathbf{F}(\mathbf{V}\hat{\mathbf{y}}; \theta).$$

- ▶ DEIM reduced order model

$$\mathbf{V}^T \mathbf{A} \mathbf{V} \hat{\mathbf{y}} + \underbrace{\mathbf{V}^T \mathbf{U} (\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \mathbf{F}(\mathbf{V}\hat{\mathbf{y}}; \theta)}_{n \times m} = \mathbf{V}^T \mathbf{b}.$$

## Selection of DEIM points

**Input:** Linearly independent vectors  $\mathbf{u}_1, \dots, \mathbf{u}_m$ .

**Output:** Indices  $p_1, \dots, p_m$ .

1.  $[\rho, p_1] = \max\{|\mathbf{u}_1|\}$
2. Set  $\mathbf{U} = [\mathbf{u}_1]$ ,  $\mathbf{P} = [\mathbf{e}_{p_1}]$ ,  $\mathbf{p} = [p_1]$
3. For  $i = 2, \dots, m$  do
  - 3.1 Solve  $(\mathbf{P}^T \mathbf{U})\mathbf{c} = \mathbf{P}^T \mathbf{u}_i$  for  $\mathbf{c}$
  - 3.2  $\mathbf{r}_i = \mathbf{u}_i - \mathbf{U}\mathbf{c}$
  - 3.3  $[\rho, p_i] = \max\{|\mathbf{r}_i|\}$
  - 3.4 Update  $\mathbf{U} = [\mathbf{U} \ \mathbf{u}_i]$ ,  $\mathbf{P} = [\mathbf{P} \ \mathbf{e}_{p_i}]$ ,  $\mathbf{p} = [\mathbf{p}^T \ p_i]^T$

**DEIM error estimate:** If  $\mathbf{U} \in \mathbb{R}^{N \times m}$  has ortho-normal columns, then

$$\|\mathbf{F} - \widehat{\mathbf{F}}\|_2 \leq \|(\mathbf{P}^T \mathbf{U})^{-1}\|_2 \|(\mathbf{I} - \mathbf{U}\mathbf{U}^T)\mathbf{F}\|_2.$$

## Why is DEIM efficient?

- ▶ DEIM approximation of nonlinearity:

$$\widehat{\mathbf{F}}(\mathbf{V}\widehat{\mathbf{y}}; \theta) \stackrel{\text{def}}{=} \mathbf{U}(\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \mathbf{F}(\mathbf{V}\widehat{\mathbf{y}}; \theta).$$

- ▶ Need to evaluate  $m$  components  $\mathbf{F}_{p_1}, \dots, \mathbf{F}_{p_m}$ .  
If they depend on  $k \approx n$  components of  $\mathbf{V}\widehat{\mathbf{y}}$ , then we only need to compute product of  $k \times n$  submatrix of  $\mathbf{V}$  times  $\widehat{\mathbf{y}}$ .

## Why is DEIM efficient?

- ▶ DEIM approximation of nonlinearity:

$$\widehat{\mathbf{F}}(\mathbf{V}\widehat{\mathbf{y}}; \theta) \stackrel{\text{def}}{=} \mathbf{U}(\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \mathbf{F}(\mathbf{V}\widehat{\mathbf{y}}; \theta).$$

- ▶ Need to evaluate  $m$  components  $\mathbf{F}_{p_1}, \dots, \mathbf{F}_{p_m}$ .  
If they depend on  $k \approx n$  components of  $\mathbf{V}\widehat{\mathbf{y}}$ , then we only need to compute product of  $k \times n$  submatrix of  $\mathbf{V}$  times  $\widehat{\mathbf{y}}$ .
- ▶ (Continuous nodal) FEM:

$$\mathbf{F}_i(\mathbf{y}; \theta) = F_h(y_h, \phi_i; \theta) = \int_{\Omega} f\left(\sum_{j=1}^N \mathbf{y}_j \phi_j(x), \theta\right) \phi_i(x) dx$$

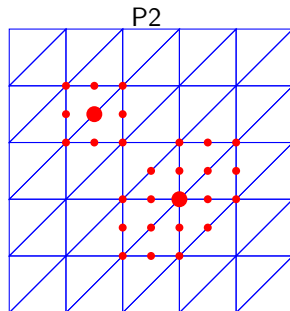
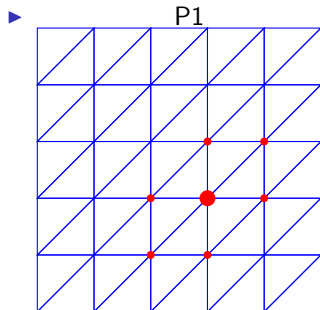
# Why is DEIM efficient?

- ▶ DEIM approximation of nonlinearity:

$$\widehat{\mathbf{F}}(\mathbf{V}\widehat{\mathbf{y}}; \theta) \stackrel{\text{def}}{=} \mathbf{U}(\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \mathbf{F}(\mathbf{V}\widehat{\mathbf{y}}; \theta).$$

- ▶ Need to evaluate  $m$  components  $\mathbf{F}_{p_1}, \dots, \mathbf{F}_{p_m}$ .  
If they depend on  $k \approx n$  components of  $\mathbf{V}\widehat{\mathbf{y}}$ , then we only need to compute product of  $k \times n$  submatrix of  $\mathbf{V}$  times  $\widehat{\mathbf{y}}$ .
- ▶ (Continuous nodal) FEM:

$$\mathbf{F}_i(\mathbf{y}; \theta) = F_h(y_h, \phi_i; \theta) = \int_{\Omega} f\left(\sum_{j=1}^N \mathbf{y}_j \phi_j(x), \theta\right) \phi_i(x) dx$$



- ▶ Alternative:

$$\mathbf{F}_i(\mathbf{y}; \theta) = \sum_{e=1}^{n_e} \int_{\Omega_e} \underbrace{f\left(\sum_{j=1}^N \mathbf{y}_j \phi_j(x); \theta\right) \phi_i(x) dx}_{\stackrel{\text{def}}{=} \mathbf{F}_i^e(\mathbf{y}; \theta)}$$

Assemble (add element information)

$$\mathbf{F}(\mathbf{y}; \theta) = \mathbf{Q} \mathbf{F}^e(\mathbf{y}; \theta)$$

where  $\mathbf{Q} \in \mathbb{R}^{N \times (n_e n_p)}$  ( $n_e$  # elements,  $n_p$  # DOF per element).

- ▶ Reduced order model applied to unassembled nonlinearity:
  - ▶ Basic model

$$\mathbf{V}^T \mathbf{A}(\mathbf{V}\hat{\mathbf{y}}) + \mathbf{V}^T \mathbf{Q} \mathbf{F}^e(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{V}^T \mathbf{b}.$$

- ▶ DEIM approximation of unassembled nonlinearity

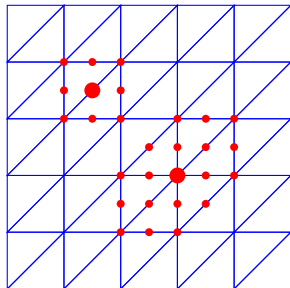
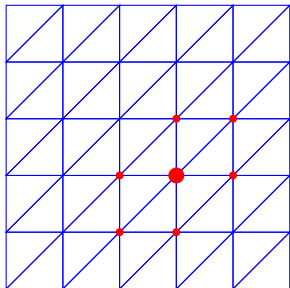
$$\hat{\mathbf{F}}^e(\mathbf{y}; \theta) = \mathbf{U}^e ((\mathbf{P}^e)^T (\mathbf{U}^e))^{-1} (\mathbf{P}^e)^T \mathbf{F}^e(\mathbf{y}; \theta).$$

- ▶ Final

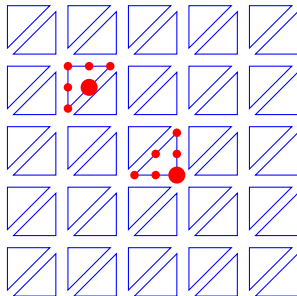
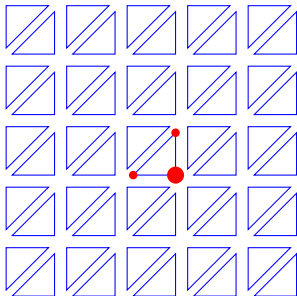
$$\mathbf{V}^T \mathbf{A} \mathbf{V} \hat{\mathbf{y}} + \left( \mathbf{V}^T \mathbf{Q} \mathbf{U}^e ((\mathbf{P}^e)^T (\mathbf{U}^e))^{-1} \right) (\mathbf{P}^e)^T \mathbf{F}^e(\mathbf{V}\hat{\mathbf{y}}; \theta) = \mathbf{V}^T \mathbf{b}.$$



## Connectivity Assembled



## Connectivity Unassembled

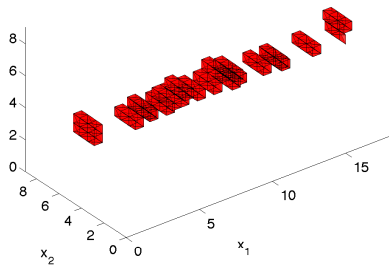


# Apply to 3D Diffusion-Advection-Reaction PDE

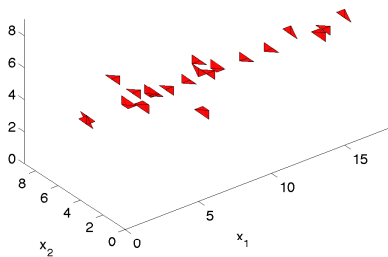
## Piecewise linear FEM

Tetrahedra that need to be evaluated

assembled



unassembled



Polynomial degree	$p = 1$			$p = 2$	
Mesh number	1	2	3	1	2
# tetrahedra	6,144	49,152	165,888	6,144	49,152
# nodes $N$	1,296	9,248	30,000	9,248	69,696
# POD basis vectors $n$	19	18	19	18	19
# DEIM points $m$	21	21	22	21	22
# nodes adjacent DEIM pts.	183	271	320	445	559
# DEIM points $m^e$	21	21	22	21	22
# nodes adjacent DEIM pts.	67	80	88	193	220

- ▶ Works with nonlinearity  $f(y, \theta)$
- ▶ Variational form

$$\begin{aligned} \mathbf{F}(\mathbf{y}; \theta)_i &= F_h(y_h, \phi; \theta) \\ &= \sum_{\ell=1}^{n_q} \varpi_{\ell} f(y_h(x_{\ell}), \theta) \phi_i(x_{\ell}) \left( \approx \int_{\Omega} f(y_h(x), \theta) \phi_i(x) dx \right) \end{aligned}$$

- ▶ Define

$$\Phi = \begin{pmatrix} \phi_1(\xi_1) & \dots & \phi_1(\xi_{n_q}) \\ \vdots & & \vdots \\ \phi_N(\xi_1) & \dots & \phi_N(\xi_{n_q}) \end{pmatrix} \in \mathbb{R}^{N \times n_q},$$

$$\mathbf{W} = \text{diag}(\varpi_1, \dots, \varpi_{n_q}),$$

$$y_h = (y_h(x_1), \dots, y_h(x_{n_q}))^T,$$

$$\mathbf{f}(y_h; \theta) = (f(y_h(x_1), \theta), \dots, f(y_h(x_{n_q}), \theta))^T$$

- ▶ FEM approx. at all quadrature points:  $y_h = \Phi^T \mathbf{y}$ .  
Matrix form of nonlinearity  $\mathbf{F}(\mathbf{y}; \theta) = \Phi^T \mathbf{W} \mathbf{f}(y_h; \theta)$ .

- ▶ Generate subspace  $\tilde{\mathbf{U}} = [\tilde{\mathbf{u}}_1, \dots, \tilde{\mathbf{u}}_m] \in \mathbb{R}^{N \times n_q}$  for nonlinear term. Want  $\mathbf{f}(y_h(\theta); \theta) \in R(\tilde{\mathbf{U}})$  approximately for all  $\theta \in \Theta$ .
- ▶ Compute approximation  $\tilde{\mathbf{f}}(y_h(\theta); \theta) = \tilde{\mathbf{U}}\mathbf{c}(y_h(\theta); \theta)$  such that  $\tilde{\mathbf{f}}(y_h(x_i); \theta) = \mathbf{f}(y_h(x_i); \theta)$  for components/quadr. points  $i = \tilde{p}_1, \dots, \tilde{p}_m$ .
- ▶ Define  $\tilde{\mathbf{P}} = [\mathbf{e}_{\tilde{p}_1}, \dots, \mathbf{e}_{\tilde{p}_m}] \in \mathbb{R}^{N \times n_q}$ ; write interpolation condition as

$$\tilde{\mathbf{P}}^T \tilde{\mathbf{f}}(y_h; \theta) = \tilde{\mathbf{P}}^T \mathbf{f}(y_h; \theta).$$

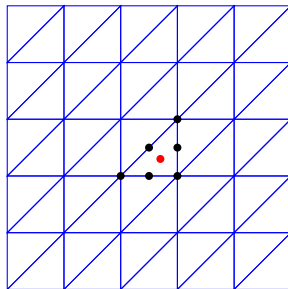
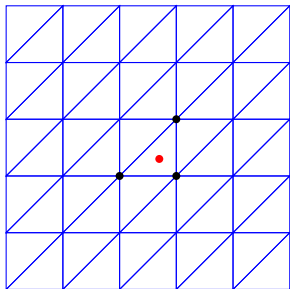
- ▶ EIM approximation of nonlinearity:

$$\tilde{\mathbf{f}}(\hat{y}_h; \theta) \stackrel{\text{def}}{=} \tilde{\mathbf{U}}(\tilde{\mathbf{P}}^T \tilde{\mathbf{U}})^{-1} \tilde{\mathbf{P}}^T \mathbf{f}(\mathbf{V}\hat{y}_h; \theta).$$

- ▶ FEM approx. at all quadrature points:  $y_h = \Phi^T \mathbf{y}$ ,  $\hat{y}_h = \Phi^T \mathbf{V}\hat{\mathbf{y}}$ . At EIM quad. points  $i = \tilde{p}_1, \dots, \tilde{p}_m$ :  $\mathbf{Q}\Phi^T \mathbf{V}\hat{\mathbf{y}}$ .
- ▶ EIM reduced order model

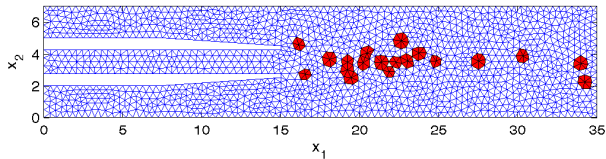
$$\mathbf{V}^T \mathbf{A} \mathbf{V} \hat{\mathbf{y}} + \underbrace{\mathbf{V}^T \Phi^T \mathbf{W} \tilde{\mathbf{U}} (\tilde{\mathbf{P}}^T \tilde{\mathbf{U}})^{-1}}_{n \times m} \tilde{\mathbf{P}}^T \mathbf{f}(\Phi^T \mathbf{V} \hat{\mathbf{y}}; \theta) = \mathbf{V}^T \mathbf{b}.$$

Evaluations • for EIM (quadrature) point •

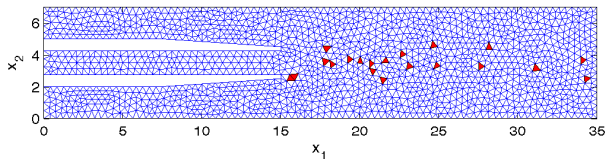


# Apply to 2D Diffusion-Advection-Reaction PDE

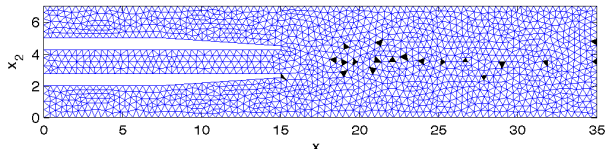
piecewise linear FEM - DEIM



piecewise linear FEM - DEIM unassembled nonlinearity



piecewise linear FEM- EIM

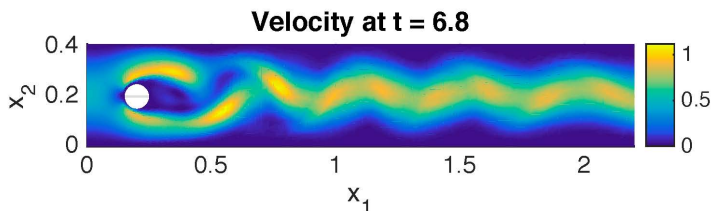


Polynomial degree	$p = 1$			$p = 2$		
Mesh number	2	3	4	2	3	4
# triangles	3,213	12,976	53,120	3,213	12,976	53,120
# nodes $N$	1,768	6,813	27,215	6,751	26,604	107,552
# POD basis vectors $n$	16	17	17	17	17	17
# DEIM points $m$	19	20	20	20	20	20
# nodes adjacent DEIM pts.	130	160	162	168	177	180
# DEIM-u points $m^e$	20	20	20	20	20	20
# nodes adjacent DEIM-u pts.	56	60	60	114	120	120
# EIM points $m$	20	20	20	20	20	20



# DEIM for Navier-Stokes

$$\begin{aligned} \frac{\partial}{\partial t} v(x, t) - \nu \Delta v(x, t) \\ + (v(x, t) \cdot \nabla) v(x, t) + \nabla p(x, t) &= 0, & \text{in } \Omega \times [0, T], \\ \nabla \cdot v(x, t) &= 0, & \text{in } \Omega \times [0, T], \\ v(x, t) &= g(x, t), & \text{on } \Gamma_{in} \times [0, T], \\ v(x, t) &= 0, & \text{on } \Gamma_D \times [0, T], \\ (\nabla v(x, t) - p(x, t)I)n(x) &= 0, & \text{on } \Gamma_{out} \times [0, T]. \end{aligned}$$



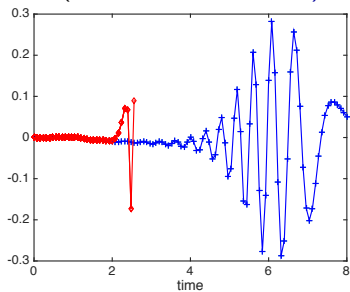
Set-up as in V. John (2004)

- ▶ Taylor-Hood P2-P1 finite elements leads to

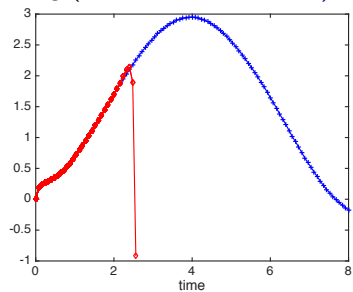
$$\mathbf{M} \frac{d}{dt} \mathbf{v}(t) + \mathbf{A} \mathbf{v}(t) + \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) + \mathbf{B}^T \mathbf{p}(t) = \mathbf{f}(t),$$
$$\mathbf{B} \mathbf{v}(t) = \mathbf{g}(t),$$
$$\mathbf{v}(0) = \mathbf{0}.$$

- ▶ Treat  $\mathbf{v}(t) \mapsto \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t)$  as general nonlinear term with DEIM

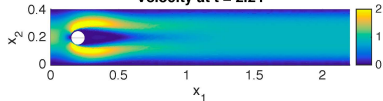
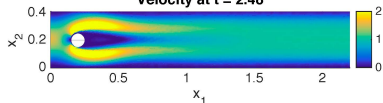
Lift (— full; — POD-DEIM)



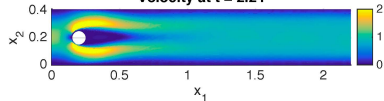
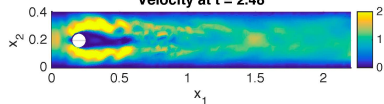
Drag (— full; — POD-DEIM)



full

Velocity at  $t = 2.24$ Velocity at  $t = 2.48$ 

POD-DEIM

Velocity at  $t = 2.24$ Velocity at  $t = 2.48$ 

- ▶ Have that

$$\int_{\Omega} (v(x) \cdot \nabla) w(x) \cdot w(x) dx = 0 \quad \text{for all } v \in [H^1(\Omega)]^2, w \in [H_0^1(\Omega)]^2$$

with  $\nabla \cdot v(x) = 0$  in  $\Omega$ .

- ▶ For Navier-Stokes with Dirichlet BCs everywhere,

$$\int_{\Omega} v^2(x, T) dx + \nu \int_0^T \int_{\Omega} \|\nabla v(x, t)\|^2 dx dt \leq \int_{\Omega} v^2(x, 0) dx + \int_0^T \int_{\Omega} \|f(x, t)\|^2 dx dt$$

(Dropped several constants.)

- ▶ If discretely,  $\mathbf{v}(t)^T \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) = 0$ ,

$$\|\mathbf{v}(T)\|^2 + \int_0^T \mathbf{v}(t)^T \mathbf{A} \mathbf{v}(t) dt \leq \|\mathbf{v}(0)\|^2 + \int_0^T \int_0^T \|\mathbf{f}(t)\|^2 dt$$

- ▶ Have that

$$\int_{\Omega} (v(x) \cdot \nabla) w(x) \cdot w(x) dx = 0 \quad \text{for all } v \in [H^1(\Omega)]^2, w \in [H_0^1(\Omega)]^2$$

with  $\nabla \cdot v(x) = 0$  in  $\Omega$ .

- ▶ For Navier-Stokes with Dirichlet BCs everywhere,

$$\int_{\Omega} v^2(x, T) dx + \nu \int_0^T \int_{\Omega} \|\nabla v(x, t)\|^2 dx dt \leq \int_{\Omega} v^2(x, 0) dx + \int_0^T \int_{\Omega} \|f(x, t)\|^2 dx dt$$

(Dropped several constants.)

- ▶ If discretely,  $\mathbf{v}(t)^T \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) = 0$ ,

$$\|\mathbf{v}(T)\|^2 + \int_0^T \mathbf{v}(t)^T \mathbf{A} \mathbf{v}(t) dt \leq \|\mathbf{v}(0)\|^2 + \int_0^T \int_0^T \|\mathbf{f}(t)\|^2 dt$$

- ▶ If  $\mathbf{v}(t)^T \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) = 0$  for all snapshots, then  $(\mathbf{V} \hat{\mathbf{v}}(t))^T \mathbf{N}(\mathbf{V} \hat{\mathbf{v}}(t)) \mathbf{V} \hat{\mathbf{v}}(t) = 0$  for POD.

- ▶ Have that

$$\int_{\Omega} (v(x) \cdot \nabla) w(x) \cdot w(x) dx = 0 \quad \text{for all } v \in [H^1(\Omega)]^2, w \in [H_0^1(\Omega)]^2$$

with  $\nabla \cdot v(x) = 0$  in  $\Omega$ .

- ▶ For Navier-Stokes with Dirichlet BCs everywhere,

$$\int_{\Omega} v^2(x, T) dx + \nu \int_0^T \int_{\Omega} \|\nabla v(x, t)\|^2 dx dt \leq \int_{\Omega} v^2(x, 0) dx + \int_0^T \int_{\Omega} \|f(x, t)\|^2 dx dt$$

(Dropped several constants.)

- ▶ If discretely,  $\mathbf{v}(t)^T \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) = 0$ ,

$$\|\mathbf{v}(T)\|^2 + \int_0^T \mathbf{v}(t)^T \mathbf{A} \mathbf{v}(t) dt \leq \|\mathbf{v}(0)\|^2 + \int_0^T \int_0^T \|\mathbf{f}(t)\|^2 dt$$

- ▶ If  $\mathbf{v}(t)^T \mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) = 0$  for all snapshots, then

$(\mathbf{V} \hat{\mathbf{v}}(t))^T \mathbf{N}(\mathbf{V} \hat{\mathbf{v}}(t)) \mathbf{V} \hat{\mathbf{v}}(t) = 0$  for POD.

- ▶ DEIM approximation of nonlinearity:

$$\mathbf{N}(\mathbf{v}(t)) \mathbf{v}(t) \approx \mathbf{U} (\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \left( \mathbf{N}(\mathbf{V} \hat{\mathbf{v}}(t)) \mathbf{V} \hat{\mathbf{v}}(t) \right).$$

In general

$$\hat{\mathbf{v}}(t) \mathbf{V}^T \mathbf{U} (\mathbf{P}^T \mathbf{U})^{-1} \mathbf{P}^T \left( \mathbf{N}(\mathbf{V} \hat{\mathbf{v}}(t)) \mathbf{V} \hat{\mathbf{v}}(t) \right) \neq 0.$$

# Outline

Motivation

EIM and DEIM

EIM and DEIM for Finite Element Simulations

EIM and DEIM for Navier-Stokes

Error Estimate

# Error Estimate

- ▶ Original problem  $\mathbf{G}(\mathbf{y}, \theta) = \mathbf{A}\mathbf{y} + \mathbf{F}(\mathbf{y}, \theta) - \mathbf{b} = \mathbf{0}$ .  
Solution  $\mathbf{y}^*$ .
- ▶ POD-DEIM reduced order model

$$\begin{aligned} & \mathbf{V}_n^T \mathbf{G}(\bar{\mathbf{y}} + \mathbf{V}_n \hat{\mathbf{y}}, \theta) \\ &= \mathbf{V}_n^T \mathbf{A} \mathbf{V}_n \hat{\mathbf{y}} + \mathbf{V}_n^T \mathbf{U}_m (\mathbf{P}^T \mathbf{U}_m)^{-1} \mathbf{P}^T \mathbf{F}(\bar{\mathbf{y}} + \mathbf{V}_n \hat{\mathbf{y}}, \theta) \\ & \quad + \mathbf{V}_n^T \mathbf{A} \bar{\mathbf{y}} + \mathbf{V}_n^T \mathbf{b} = \mathbf{0}. \end{aligned}$$

Solution  $\hat{\mathbf{y}}^*$ .

Will drop mean  $\bar{\mathbf{y}}$  to simplify notation.

- ▶ Want estimate  $\mathbf{y}^* - \mathbf{V}_n \hat{\mathbf{y}}^*$ ; select number of bases  $\mathbf{V}_n, \mathbf{U}_m$ .



# Newton's Method

- ▶ Newton's method for the original problem

$$\begin{aligned}D_y \mathbf{G}(\mathbf{y}^k, \theta) \delta \mathbf{y}^k &= -\mathbf{G}(\mathbf{y}^k, \theta), \\ \mathbf{y}^{k+1} &= \mathbf{y}^k + \delta \mathbf{y}^k.\end{aligned}$$

- ▶ Newton's method for the POD-DEIM reduced order model

$$\begin{aligned}D_y \mathbf{V}_n^T \mathbf{F}(\mathbf{V}_n \hat{\mathbf{y}}^k, \theta) \mathbf{V}_n \delta \hat{\mathbf{y}} &= -\mathbf{V}_n^T \mathbf{F}(\mathbf{V}_n \hat{\mathbf{y}}^k, \theta), \\ \hat{\mathbf{y}}^{k+1} &= \hat{\mathbf{y}}^k + \delta \hat{\mathbf{y}}^k.\end{aligned}$$

## Newton-Kantorowich type estimates

- ▶  $\mathbf{G}(\mathbf{y}, \theta)$  cont. diff'bel ;  $D_y \mathbf{G}(\mathbf{y}, \theta)$  be invertible for all  $\mathbf{y}, \theta \in \Theta$ .
- ▶ Affine covariance Lipschitz condition

$$\|D_y \mathbf{G}(\mathbf{y}, \theta)^{-1}(D_y \mathbf{G}(\mathbf{y}, \theta) - D_y \mathbf{G}(\mathbf{v}, \theta))(\mathbf{y} - \mathbf{v})\| \leq \omega \|\mathbf{y} - \mathbf{v}\|^2 \quad \forall \mathbf{y}, \mathbf{v}.$$

- ▶  $h_0 = \omega \|\delta \mathbf{y}^0\| < 2$ .

Newton's method converges to  $\mathbf{y}^*$  with quadratic convergence rate

$$\|\mathbf{y}^{k+1} - \mathbf{y}^k\| \leq \frac{\omega}{2} \|\mathbf{y}^k - \mathbf{y}^{k-1}\|^2$$

and

$$\|\mathbf{y}^* - \mathbf{y}^0\| \leq \hat{r}_0 \stackrel{\text{def}}{=} \frac{\|\delta \mathbf{y}^0\|}{1 - \frac{1}{2} h_0}.$$

Can estimate (heuristics)

$$h_0 \approx 2\Theta_0 \quad \text{with } \Theta_0 = \|\delta \mathbf{y}^1\|_2 / \|\delta \mathbf{y}^0\|_2.$$

## Error Estimates

- ▶ Apply previous theorem to full problem with star value  $\mathbf{y}^0 = \mathbf{V}_n \hat{\mathbf{y}}^*$ :

$$\|\mathbf{y}^* - \mathbf{V}_n \hat{\mathbf{y}}^*\| \leq r_0 \stackrel{\text{def}}{=} \frac{\|\delta \mathbf{y}^0\|}{1 - \frac{1}{2} h_0}.$$

Can estimate (heuristics)

$$h_0 \approx 2\Theta_0 \quad \text{with } \Theta_0 = \|\delta \mathbf{y}^1\|_2 / \|\delta \mathbf{y}^0\|_2.$$

- ▶ Apply previous theorem to reduced order problem with star value  $\hat{\mathbf{y}}^0 = \mathbf{V}_n^T \mathbf{y}^*$ :

$$\|\hat{\mathbf{y}}^* - \mathbf{V}_n^T \mathbf{y}^*\| \leq \hat{r}_0 \stackrel{\text{def}}{=} \frac{\|\delta \hat{\mathbf{y}}^0\|}{1 - \frac{1}{2} \hat{h}_0}.$$

Can estimate (heuristics)

$$\hat{h}_0 \approx 2\hat{\Theta}_0 \quad \text{with } \hat{\Theta}_0 = \|\delta \hat{\mathbf{y}}^1\|_2 / \|\delta \hat{\mathbf{y}}^0\|_2.$$

# Heuristic Algorithm

INPUT: Newton tolerance:  $\tau_{new}$ , max. Newton iterations:  $k_{max}$ ,  
tolerance:  $\tau_{est}$ ,

initial size of basis:  $n$ , max. size basis:  $n_{max} > n$ ,

initial Newton iterate:  $\hat{\mathbf{y}}^0$

OUTPUT:  $r_0$ ,  $\mathbf{V}_n$

**while**  $n \leq n_{max}$

- ▶ Generate reduced order model  $\mathbf{V}_n$ ,  $\mathbf{U}_m$
- ▶ Apply Newton's method to compute  $\hat{\mathbf{y}}^*$ .
- ▶ Estimate error (full estimator)
  - ▶ Set  $\mathbf{y}^0 = \bar{\mathbf{y}} + \mathbf{V}_n \hat{\mathbf{y}}^*$
  - ▶ Compute  $\Theta_0 = \frac{\|\delta \mathbf{y}^1\|_2}{\|\delta \mathbf{y}^0\|_2}$ ,  $r_0 = \frac{\|\delta \mathbf{y}^0\|_2}{1 - \Theta_0}$
  - ▶ **If**  $r_0 \leq \tau_{est}$ , **STOP (outer loop)**
  - ▶ **else if**  $n + 1 > n_{max}$ , **update** basis  $\mathbf{V}_{n_{max}}$  .
  - ▶ **else** set  $n = n + 1$  goto 'while' loop
  - ▶ Compute the new iterate  $\mathbf{y}^2 = \mathbf{y}^1 + \delta \mathbf{y}^1$ .
  - ▶  $\hat{\mathbf{y}}^0 = \mathbf{V}_n^T \mathbf{y}^2$ .
- ▶ Estimate error (reduced estimator)  
Use reduced order problem with  $\mathbf{V}_{n_{max}}$  instead of full order problem.

**end**

## Application to 3D Reaction diffusion

Grid 1		Grid 2		Grid 3	
$n$	$m$	$n$	$m$	$n$	$m$
6	8	6	8	6	8
9	12	9	12	9	13
13	15	13	15	13	17
17	20	17	20	18	21
-	-	-	-	21	24

# basis vectors  $n$  and # of DEIM points  $m$  for three different grids.

Grid 1		Grid 2		Grid 3	
estimate	actual (full)	estimate	actual (full)	estimate	actual (full)
$3.53 \times 10^{-2}$	$3.46 \times 10^{-2}$	$1.54 \times 10^{-2}$	$1.54 \times 10^{-2}$	$3.12 \times 10^{-1}$	$3.02 \times 10^{-1}$
$2.22 \times 10^{-3}$	$2.22 \times 10^{-3}$	$5.23 \times 10^{-3}$	$5.23 \times 10^{-3}$	$1.66 \times 10^{-2}$	$1.66 \times 10^{-2}$
$5.27 \times 10^{-4}$	$5.27 \times 10^{-4}$	$2.29 \times 10^{-3}$	$2.28 \times 10^{-3}$	$8.95 \times 10^{-3}$	$8.94 \times 10^{-3}$
-	-	$2.77 \times 10^{-4}$	$2.77 \times 10^{-4}$	$1.72 \times 10^{-3}$	$1.71 \times 10^{-3}$
-	-	-	-	$9.47 \times 10^{-4}$	$9.47 \times 10^{-4}$

Error estimator for three different grids using  $\tau_{est} = 5 \times 10^{-4}$ .

## Conclusions:

- ▶ Comparison of DEIM and EIM for FEM computations
- ▶ Capture properties of full order problem in reduced order model.
- ▶ Newton-based error estimates